An MPL-CCN Model for Real-time Health Monitoring and Intervention

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ABSTRACT

The use of Artificial Intelligence (AI) in healthcare, particularly in real-time health monitoring and predictive interventions for chronic diseases, has many benefits but also many drawbacks. Existing health risk prediction algorithms face accuracy issues and, due to the wide variety of health profiles, general algorithm applicability is problematic. The proposed model solves this issue by using an advanced AI framework to improve the accuracy of the prediction of Chronic Kidney Disease (CKD) and eliminate false positives. Our hybrid Deep Learning (DL) method blends a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN), thus including real-time feedback to help the system learn from its predictions and results. The proposed system solves a major problem in this area and sets a new benchmark for AI applications in healthcare by directly addressing prediction accuracy. It offers more tailored, accurate, and responsive chronic disease management, improving patient outcomes and healthcare resource efficiency.

Keywords - artificial intelligence; healthcare; predictive intervention; deep learning; adaptive learning systems; chronic diseases; CKD

I. INTRODUCTION

With the introduction of AI to the medical field, new standards in patient management, diagnosis, and treatment have been set, marking a watershed moment in healthcare's development. Medical researchers have been able to tap into new avenues of inquiry, enhance diagnostic accuracy, and personalize patient treatment because AI's ability to efficiently and accurately sift through and analyze massive datasets. Utilizing intricate algorithms for early disease diagnosis and Machine Learning (ML) models for patient health outcome prediction, AI is playing a crucial and revolutionary role in healthcare, laying the groundwork for future medical breakthroughs [1]. AI has far-reaching and significant implications in the medical field. The development of AI-enhanced imaging software, which reduces human error and improves patient outcomes by accurately interpreting X-rays and MRIs, is one example of the advanced diagnostic tools made possible by this technology. AI is also driving the field of personalized medicine, which optimizes treatment...
strategies for individual patients by collecting and analyzing their unique health data, genetic makeup, and lifestyle [2]. In addition, chatbots and virtual assistants powered by AI are rapidly becoming an essential part of patient care. They offer round-the-clock assistance, medication reminders, and answers to health-related questions, all of which increase patient involvement and adherence to treatment plans. Despite these developments, AI application in healthcare faces many challenges. AI in healthcare relies on accurate predictions. Data biases or poor training datasets might degrade its accuracy, resulting in inaccurate diagnoses or treatment recommendations. Due to their inability to adapt to new data or patient health changes, many present AI systems are unsuitable for real-time, dynamic tasks like health monitoring and emergency response.

Regarding diabetes prediction, SVM models have been commonly utilized [3, 4]. Due to their processing cost, SVMs are not always the most efficient models for real-time prediction, especially with big datasets. Finally, SVMs may struggle with diabetes' biologically complex and non-linear feature-relationships.

Decision Trees (DTs) are among the most well-known ML tools for classification and regression. In [5], DTs were utilized to categorize people into several risk groups according to their health data, which includes age, blood pressure, cholesterol levels, smoking status, and other pertinent clinical characteristics when it comes to detecting heart diseases. DTs' key benefits are their simplicity and interpretability but have the reliability problem of being very sensitive to changes in the data, which can cause huge shifts in the tree structure [6]. Unlike DTs, the proposed uses a network of neurons that can learn complex, nonlinear data relationships without assuming feature independence.

When there are many independent variables in a dataset, Logistic Regression (LR) is a useful statistical tool for examining the relationships between them. A dichotomous variable, which can only take one of two potential values, is used to measure the outcome. LR can be employed to estimate the probabilities of Chronic Kidney Disease (CKD) progression to advanced stages given a number of variables, including age, blood pressure, serum creatinine levels, diabetes, and cardiovascular disease [7]. The model in [7] predicts the event's probability of occurrence (i.e. CKD progression) by fitting a logistic function—an S-shaped curve—to the data. A logistic (sigmoid) function is used to provide a probability score between 0 and 1, after which the input features are linearly combined by this function. Timely and focused interventions can be made possible by this score, which predicts the chance of a patient's disease developing.

Despite its popularity due to its simplicity and interpretability, LR has severe limitations in predicting CKD. Its key assumption is that the input variables and the output log probability are linear [8]. This assumption may be oversimplified for complex situations like CKD, where factors interact non-linearly. LR cannot handle complex and non-linear associations without transforming the variables, which requires domain expertise and model complexity. Medical datasets have many related variables, which might produce predictor collinearity, which LR cannot manage [9, 10]. This restriction may distort estimates of factors' relative relevance in predicting sickness.

In this paper, an AI framework with complicated hybrid analysis and adaptive learning algorithms to address these difficulties is proposed. By tailoring health monitoring and activities to each person's health profile, this strategy enhances forecast accuracy and reliability while responding to new data. Our feedback-based algorithm improvement provides more precise, timely, and effective actions, revolutionizing personalized healthcare.

The proposed DL model automatically captures nonlinear interactions among numerous factors, eliminating the need to manually convert features. DL networks handle complex and non-linear interactions better by automatically learning the optimum data representation for prediction. This talent improves our prediction and clinical decision-making by helping us understand CKD condition. DL's data-processing and learning skills allow the model to adapt to new input and improve its predictions [11]. Our DL algorithm can automatically generate hierarchical data representations, making it better than SVMs at detecting intricate and non-linear feature correlations. DL algorithms, especially multi-layered ones, can process and integrate many health indices to capture the complex patterns and interactions that define diabetes development and progression. This allows more exact and personalized projections because diabetes presents differently in each person. DL models are more dynamic and scalable than SVMs and can handle larger datasets. Logistic Regression for CKD Progression

II. THE PROPOSED SYSTEM

In healthcare, AI is set to redefine real-time health monitoring and predictive interventions for chronic diseases. Traditional methods falter due to their simplistic assumptions and a generalized approach that fails to account for individual variability. These shortcomings manifest in inaccuracies and the inability to precisely predict health risks, resulting in either unnecessary anxiety or overlooked conditions due to false positives and negatives. Moreover, the diversity of individual health profiles presents a significant challenge for the universal applicability of predictive algorithms. Our proposed model leverages an advanced AI framework, employing a hybrid DL strategy that synergizes patient-specific data with broader health trends, aiming to significantly enhance prediction accuracy and minimize false alerts.

\[
Risk\ Prediction\ Error = \frac{1}{N} \sum_{i=1}^{N} (Predicted\ Risk_i - Actual\ Risk_i)^2
\]

(1)

\[
False\ Positive\ Rate = \frac{FP}{FP+TN}
\]

(2)

\[
False\ Negative\ Rate = \frac{FN}{FN+TP}
\]

(3)

To circumvent the limitations of conventional models like LR, which simplifies the intricate dynamics of variables into a linear relationship, our approach adopts DL, which excels in identifying complex, nonlinear interactions among variables, offering a deeper understanding of disease progression. The
proposed DL model capitalizes on multiple layers of neural networks, employing activation functions such as the Rectified Linear Unit (ReLU) to process data, effectively capturing the nuanced relationships within the health data.

\[
ReL U(x) = \max(0, x) \quad (4)
\]

\[
\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (5)
\]

\[
\text{Loss Function} = \frac{1}{N} \sum_{i=1}^{N} [y_i \log(y'_i) + (1 - y_i) \log(1 - y'_i)] \quad (6)
\]

The dataset of clinical records undergoes rigorous preprocessing, including normalization to ensure uniformity across the feature set \( X' = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \). Feature selection harnesses techniques like mutual information to discern the most predictive variables for CKD, while feature engineering generates new features capturing complex disease progression patterns.

Normalized Feature = \( \frac{\text{Feature} - \text{Feature}_{\text{min}}}{\text{Feature}_{\text{max}} - \text{Feature}_{\text{min}}} \) \quad (7)

\( I(X; Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \left( \frac{p(x|y)}{p(x)} \right) \) \quad (8)

Engineered Feature = \( \frac{\text{Feature}_{\text{A}}}{\text{Feature}_{\text{B}+\epsilon}} \) \quad (9)

The model's architecture is well-thought-out; it uses a Multi-Layer Perceptron (MLP) with ReLU activation functions to render linearity non-existent and overfitting prevention layers to avoid it. The model is fine-tuned for prediction by training it on a large dataset and then uses the Adam optimization rule. This algorithm is quite complex. It modifies the neural network's weights in order to minimize the loss function, considering both the parameter gradients and the momentum of prior updates.

The model then uses the sigmoid activation function to provide predictions, which indicate the chance of CKD progression in a patient as a probability between 0 and 1. Wherever the model's predictions differ from the anticipated results, a Feedback Adjustment phase is utilized. Important for the model's error-reduction capabilities, this stage involves shifting weights in a way that improves future predictions. The Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC) assesses the model's ability to discriminate between classes; it is one of the metrics computed to assess the model's performance. Additionally, we calculate the model's sensitivity to learn about its performance with respect to genuine positive rates and specificity to learn about its capacity to avoid false positives. In the medical industry, where both false positives and negatives can have serious implications, the F1 Score plays a vital role in achieving a balance between sensitivity and precision, which is measured by the accuracy of the model's positive predictions.

**Proposed Algorithm:**

**Step 1:**

\[
\text{Binary Cross-Entropy Loss} = \frac{1}{N} \sum_{i=1}^{N} [y_i \log(y'_i) + (1 - y_i) \log(1 - y'_i)]
\]

**Step 2:**

\[
\text{Adam Update Rule} = \theta_{\text{next step}} = \theta_{\text{previous step}} - \mu \cdot \nabla \ell(\theta)
\]

**Step 3:**

**Model Prediction** = \( \sigma(W \cdot X + b) \)

**Step 4:**

Feedback Adjustment = \( W_{\text{new}} = W_{\text{old}} + \alpha \cdot (\text{Target Output} - \text{Model Output}) \cdot X \)

**Step 5:**

**Model Evaluation Metric** = \( \frac{1}{N} \sum_{i=1}^{N} I(y'_i = y_i) \)

**Step 6:**

Sensitivity = \( \frac{TP}{TP + FN} \)

**Step 7:**

Specificity = \( \frac{TN}{TN + FP} \)

**Step 8:**

Precision = \( \frac{TP}{TP + FP} \)

**Step 9:**

F1 Score = \( \frac{2 \cdot \text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \)

**Step 10:**

Model Update Frequency = \( \frac{\text{Number of Epochs}}{\text{Improvement Threshold}} \)

**Step 11:**

Data Augmentation = \( X_{\text{aug}} = f(x) \)

**Step 12:**

Hyperparameter Tuning = \( \arg \min_{\lambda} \text{Validation loss}(\lambda) \)

**Step 13:**
Regularization Technique Application = \lambda \sum_{i=1}^{n} \theta_i^2

Step 14:
Model Deployment Readiness Score = \frac{\text{Number of Successful Predictions}}{\text{Total Predictions}}

Step 15:
Continuous Monitoring Metric = \frac{\text{Sum of deviations in Predictions over time}}{\text{Number of Predictions}}

Step 16:
Patient Outcome Improvement Rate = \frac{\text{Number of Improved Outcome Post Interventions}}{\text{Total interventions}}

In addition to these core performance metrics, the algorithm also factors in Model Update Frequency to determine how often it needs retraining to maintain its accuracy as new data becomes available. This is a pragmatic approach in the rapidly evolving field of healthcare where patient data and disease patterns can change over time. Data augmentation is conducted to artificially expand the dataset, which helps in improving the model's robustness by providing a more varied set of scenarios for the model to learn from.

The subsequent steps introduce advanced strategies to refine the model further. Hyperparameter tuning is utilized to find the optimal settings for the model's parameters that lead to the best performance on the validation dataset, a crucial step to prevent overfitting and to ensure that the model generalizes well to new, unseen data. The regularization technique application is another safeguard against overfitting, penalizing the complexity of the model by adding a regularization term to the loss function, which helps in the development of a more generalized model.

A unique aspect of this algorithm is the consideration of a Model Deployment Readiness Score, which assesses whether the model is performing at a level suitable for real-world application. This ensures that only well-performing models are deployed in clinical settings, safeguarding patient care. Once deployed, Continuous Monitoring Metrics are utilized to track the model's performance over time, ensuring that any degradation in accuracy is swiftly identified and addressed. Finally, the algorithm calculates the Patient Outcome Improvement Rate, directly correlating the model's predictions with patient health outcomes to quantify the model's impact in practical terms. This rate is a direct measure of the model's efficacy in contributing to improved healthcare interventions and patient care.

In summary, the algorithm provides a detailed framework for the development, evaluation, and deployment of a deep learning model for CKD prediction. It meticulously balances the technical aspects of ML, such as loss functions and optimization algorithms, with the practical needs of healthcare delivery, such as sensitivity to patient outcomes and adaptability to new data. The resulting model promises not only to enhance the predictive accuracy in healthcare settings but also to evolve continuously in response to an ever-changing medical landscape, driving forward the potential of AI to deliver personalized, responsive care and to improve patient outcomes significant. The sample dataset used for proposed model is represented in Table I.

| TABLE I. THE SAMPLE DATASET USED IN THE PROPOSED MODEL |
| Age | 58 | 48 | 54 | 55 | 56 | 57 | 58 | 59 | 60 |
| Gender | F | M | F | M | F | M | F | M | F |
| BP | 162 | 145 | 111 | 160 | 110 | 162 | 135 | 121 | 159 |
| Albumin | 1 | 3 | 0 | 2 | 4 | 2 | 3 | 2 | 1 |
| Sugar | 3 | 5 | 2 | 0 | 4 | 1 | 4 | 3 | 1 |
| Blood urea | 71 | 88 | 18 | 45 | 58 | 16 | 69 | 31 | 65 |
| Serum creatinine | 1.87 | 4.75 | 7.03 | 2.93 | 3.24 | 2.87 | 4.65 | 3.43 | 4.33 |
| Hypertension | No | Yes | No | No | Yes | No | Yes | No | No |
| Diabetes mellitus | No | No | No | Yes | Yes | No | No | No | Yes |
| Appetite | Good | Good | Poor | Poor | Good | Good | Good | Poor | Poor |
| Pedal edema | No | No | Yes | Yes | No | No | No | No | Yes |
| Anemia | No | Yes | No | Yes | Yes | No | Yes | No | Yes |
| Sodium | 140.2 | 141.4 | 131.9 | 132.7 | 139.6 | 163.1 | 153.4 | 121.9 | 137.8 |
| Potassium | 5.42 | 3.91 | 4.68 | 4.91 | 5.14 | 6.32 | 8.54 | 3.73 | 5.12 |
| Score | 0.323 | 0.732 | 0.445 | 0.575 | 0.612 | 0.387 | 0.723 | 0.494 | 0.634 |
| Class | NoCDK | CDK | NoCDK | CDK | CDK | NoCDK | CDK | NoCDK | CDK |

III. RESULTS

With a special emphasis on CKD, our AI framework, built around a DL architecture, has been painstakingly modified to meet the demands of real-time health monitoring for chronic illnesses. The model claims to greatly improve forecast accuracy and decrease false alarms by using a hybrid approach that combines patient-specific data with large population health trends. It has an adaptive learning process that is driven by real-time feedback, so the model can continuously improve its predictions based on the results of its interventions. The proposed model was compared to two popular methods in the domain, the standard LR model and the RF algorithm. The complicated, non-linear correlations common in medical data might be difficult for LR to handle, despite its popularity in medical statistics due to its interpretability and simplicity. In contrast, RF provides stronger performance by combining numerous DTs to better manage non-linearity; yet, it could not
Addressing a significant knowledge gap in chronic disease management, this study presents an innovative AI model designed to enhance predictive accuracy and patient outcomes. The proposed AI model significantly enhances chronic disease management through its advanced predictive capabilities. Compared to more traditional approaches, such as Logistic Regression and Random Forest, the suggested AI model performs better across a number of important measures, establishing a new standard for real-time health monitoring. It has the potential to completely transform patient care with its advanced deep learning framework, which greatly improves the accuracy of predictions for chronic diseases like CKD. The model exemplifies the power of machine learning in healthcare by reliably outperforming traditional methods in terms of both recall and precision.

In conclusion, this work not only fills a crucial gap in predictive healthcare but also introduces a novel application of deep learning in chronic disease management. By outperforming existing models in precision and recall, our AI model sets a new benchmark for future research. This demonstrates how AI has the ability to revolutionize healthcare by improving both patient outcomes and system efficiency. In the future, these models will be essential in creating healthcare solutions that are more proactive and tailored to each individual's needs.

REFERENCES


